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Economic, policy, social, and regulatory aspects of AI-driven smart buildings

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ABSTRACT

The significance of this research depends on the fact that it thoroughly investigates the effective implementation of advanced technologies in smart buildings particularly automated systems in buildings, sensors, and data analytics, to enhance operational efficiency, occupant comfort, and sustainability associated with the incorporation of artificial intelligence (AI) technology into Building Management Systems (BMS). Improving the building's efficiency, sustainability, and the occupants' comfort is a prime goal of this research. However while attaining this, certain obstacles such as socioeconomic inequalities, data privacy protection, negotiating regulatory landscapes, and providing effective access to all the smart technologies make hurdles that need to be overcome and rectified. The Integrated AI-Driven Smart Buildings Framework (IAI-DSBF) is a novel strategy that has been modeled and implemented to tackle, analyze, and set out the possibilities intelligently to the user to make a necessary action and in some instant, it decides itself and makes the logical action which needs for the moment. The IAI-DSBF provides a methodical approach to managing smart buildings' monetary, societal, and regulatory components, economic growth, effective policymaking, social inclusion, and navigating regulatory complexity can all be achieved using this model with the aid of artificial intelligence. This all-encompassing method makes it easier to create smart building ecosystems that emphasize openness, responsibility, and the general welfare of society. Our simulation results show that the suggested framework effectively improves building performance measures, increases compliance with regulations, and encourages community involvement by analyzing the data from the smart-building system Kaggle dataset. Urban planning, energy management, public health, and disaster response are a few fields that have been useful for the IAI-DSBF. The proposed IAI-DSBF increases the building performance ratio of 99.1 %, community involvement ratio of 98.5 %, economic growth ratio of 99.12 %, sustainability ratio of 98.2 %, and resilience ratio of 97.5 % compared to other pre-existing models. By adopting this integrated approach, stakeholders can fully utilize smart technologies to build sustainable and resilient communities and cities.

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Nomenclature

Parameter	Description
α	Policy limitations
$\forall$	Social consequences
b_j	Economic benefits
j	Smart building element
u	Situations
D	Demand
∂	Effectiveness parameters
t	Costs over time
ck	Cost
kQ^{wu}	Operational advantages
$U(a)$	Weights
$v_{j,u}$	Smart building component
$Q_{j,k}$	Adjusted demand
A_j	Collection of actions
$b_{p\sim r_k,}$	Advantages
$\forall^u s_p$	Limitations
J_k	Effects on a certain set
F	Objective function

1. Introduction

Artificial intelligence (AI) is the term used to describe a group of computer programs that carry out activities often performed by humans. It attains human awareness, reasoning, interaction, and learning levels, matching or surpassing human intelligence [1]. Artificial intelligence systems in intelligent machines have the same ability to modify their behavior without intentional reprogramming as human beings [2]. The capacity to absorb information from one's surroundings and apply it to circumstances not experienced up to that point may be considered intelligence [3]. Answering complicated issues that call for intellectual input is feasible using AI as a science. AI takes many different shapes in contemporary society [4]. Algorithms are used to examine data since machines are designed to recognize certain patterns in datasets. AI uses learning based on experience to offer reinforcement [5].

The field of computer science, artificial intelligence (AI), attempts to develop computer programs that can replicate human intellect to complete specific tasks. Among these responsibilities are the ability to make decisions, see patterns, interpret conversations, and solve problems. To give a thorough picture, it is also vital to distinguish between various types of AI. Weak AI, or narrow AI, describes systems only trained to carry out a limited number of tasks. Many modern apps rely on this AI, including streaming services' recommendation systems and virtual assistants like Alexa and Siri. In their narrow areas, these systems excel but can't achieve much beyond what they were designed to do. General AI, often known as Strong AI, may potentially do a wide variety of activities with cognitive capacities comparable to those of humans. Since no systems yet demonstrate the degree of flexibility and comprehension typified by human intelligence, this branch of AI is primarily theoretical. Superintelligent AI provides a theoretical model of artificial intelligence that goes above and beyond human intellect in almost every area, including emotional intelligence, creativity, and problem-solving. As a being with capacities beyond human control or understanding, discussions on superintelligent AI frequently centre on ethical concerns and possible consequences.

AI facilitates essential network applications connecting mobile phones, houses, cars, workplaces, appliances, and pertinent service providers [6]. AI is widely used in the financial industry, healthcare, energy and transportation, smart cities, security, education, and food systems [7]. AI is being utilized in city planning and transportation infrastructure to reduce traffic jams, accidents, and bottlenecks via real-time analysis of driving patterns [8]. Quick technological advancements greatly impact the potential and uses of IAI-DSBF in society. Although people's fear and distrust of AI systems have indeed increased because of the perceived dangers of losing control, the potential advantages of these systems are astounding and well worth the time and effort needed to investigate the possibilities and reduce the hazards [9]. The four-layer architecture established for smart city deployment includes sensing, transmission, data management, and application levels, which are tightly tied to data collecting and analysis [10].

A sensor network, an essential component of the sensing layer, collects data from various physical devices. Convergence of all data sources and communication networks is accomplished via the transmission layer [11]. It is the job of the data management layer to store and analyze data to aid in decision-making processes. Intermediary between residents and the data management layer, the application layer stands in for all a smart city's services [12]. A few cities seem responsible for a disproportionate amount of global carbon emissions. This concentration suggests that, in numerous instances, local governments have authority over emissions on par with national governments [13]. Connectivity, object interaction, remote management, control, automation, and proactive behavior are all characteristics of a smart building [14]. The smart building idea has been discussed by several researchers, each with their own unique point of view. It encourages the construction industry to undergo a digital transformation over the next several years, and water heaters, lights, appliances, renewable power systems, and more should all be able to be controlled remotely in autonomous, smart buildings [15].

Artificial intelligence (AI) reduces expenditures by optimizing energy use, predictive maintenance, and resource allocation. Energy and safety standards are two examples of regulatory criteria that AI helps satisfy by integrating algorithms that continually adapt to legislative modifications. From a social perspective, the framework maximizes accessibility and user experience by tailoring built environments with artificial intelligence, promoting inclusion and wellness. The development of an intelligent, flexible construction environment through the potent integration of AI with various ICT technologies, including the Internet of Things (IoT), big data, cloud computing, and blockchain. With artificial intelligence, IoT sensors collect real-time data on energy consumption, occupancy, and environmental factors, allowing for better efficiency and comfort choices. The platform handles massive amounts of data using big data analytics, enabling AI to see trends in use and anticipate maintenance requirements, allowing for better use of resources. Because cloud computing permits distant data storage and processing, it is scalable, and IAI-DSBF can adjust to changing needs without investing much in local infrastructure. To the already-secure interactions between users, AI modules, and Internet of Things (IoT) devices, blockchain provides an additional defense by providing immutable records and encrypted data transfers.

IAI-DSBF employs AI-driven security measures to ensure regulation compliance, including data encryption and real-time monitoring. These measures complement data privacy legislation such as GDPR, protecting sensitive information and guaranteeing strict adherence to data protection requirements. Due to its interdependent features, incorporating AI into smart buildings has never been easier than with IAI-DSBF. To achieve optimal efficiency, the building's lighting, Heating, Ventilation, Air Conditioning(HVAC), and other systems may be dynamically adjusted thanks to AI and IoT sensors that collect and analyze real-time data on occupancy, energy usage, and environmental conditions. Predictive maintenance reduces equipment downtime and increases lifespan by spotting patterns and trends in use made possible by IAI-DSBF's big data analytics. With the recognition of cloud computing's remote monitoring and control capabilities, buildings can adapt to changing environmental conditions and user needs from anywhere. The intelligent building ecosystem is even more protected thanks to blockchain technology, which safeguards data transactions and keeps user privacy intact. The networked technologies inside IAI-DSBF create an intelligent building environment that is responsive, efficient, and safe. This environment is adapted to the demands of the inhabitants.

This paper is structured as follows: Section 1 studies the related research work of the AI-integrated smart building. Section 2 explains the proposed methodology of IAI-DSBF, and in Section 3, the performance of the IAI-DSBF is discussed and analyzed.

1.1. Related study

Humans or traditional computer systems use rule-based techniques to analyze large volumes of data, but identifying patterns in smart buildings is not practical. Thus, one of the main enablers of the construction process is AI's capacity to analyze enormous volumes of data, identify patterns, and create large-scale statistical models. AI may be used in cities to improve the energy infrastructure and build a more robust and sustainable urban future. Artificial intelligence has a lot to offer in terms of solutions for many aspects of human endeavor, including smart buildings that different technologies have analyzed.

1.1.1. Building information modeling (BIM)

Building information modeling, or BIM, is the digital foundation of the architectural, engineering, and construction sectors. Various AI systems have rapidly advanced to consistently handle vast amounts of data in complicated and unpredictable contexts. The combination of AI and BIM may provide new added value in managing construction projects with inherent complexity and unpredictability since both have garnered sustained attention. Pan, Y et al. [16] provide a thorough analysis and overview of BIM-AI integration in enhancing smart construction management to help the construction industry keep up with the rapid advancements in automation and digitalization.

1.1.2. IoT based sensors

Rane N et al. [17] explore many uses, challenges, and opportunities arising from the joint use of AI and IoT-based sensors in smart buildings. AI-enabled smart sensors allow real-time environmental, energy, and structural health monitoring in infrastructure and buildings. By enabling predictive maintenance, these solutions maximize uptime and guarantee the longevity of structures. Moreover, AI-driven analytics enhance safety procedures, expedite the construction process, and optimize resource allocation, all of which contribute to an overall increase in project efficiency.

1.1.3. Machine learning-based tools (ML-BT)

The construction sector lets designers decide with knowledge, especially in the initial design phases. This work extensively assesses the literature on machine learning-based tools supporting performance-driven design. A thorough keyword-driven search across several bibliographic databases produced a combined dataset subjected to automated analysis to identify recurring themes, relationships, and structural subtleties in the corpus of literature. The main conclusions show that master plans and neighborhood-scale simulations are becoming increasingly important, according to Di Stefano A. G. et al. [18].

1.1.4. Deep learning methods (DLM)

In smart building, DLM is applied to the following areas of construction management, progress tracking, and safety; durability, life cycle analysis, and circular economy; architectural design and visualization; material design and optimization; structural design and analysis; offsite manufacturing and automation; and construction management, building management, and health monitoring. This study offers a novel viewpoint on using DL applications in these fields across the whole building lifespan, including the stages of conception, design, construction, operation, and maintenance until the structure's end of life by Baduge, S. K et al. [19].

1.1.5. Big data (BD)

Smart and energy-conscious buildings may become a reality by fusing emerging technologies like blockchain, artificial intelligence, the Internet of Things, and big data to solve practical issues. Hernández-Moral, G. et al. [20] provide a critical analysis and a comprehensive definition of the big data value chain for the European built environment, considering a variety of needs and viewpoints, including “policy,” “technology,” and “business,” to investigate the primary obstacles and business opportunities in this field.

1.1.6. Supply chain management (SCM)

The supply chains must balance regular operations and contingency planning in the erratic economic climate. As a result, this study looks at the use of artificial intelligence in enabling supply chain resilience. This research gathered answers from 27 supply chain specialists to assess the link between various AI-enabled supply chain features and how these factors move it toward resilience. Additionally, an empirical study was carried out using the replies from 231 supply chain specialists to confirm the findings of Singh, R. K et al. [21].

1.1.7. Fuzzy neural network (FNN)

A fuzzy neural network is used to couple the projected values of these two sub-models to create the building total load forecasting model. The suggested technique is validated using a case study of an office building in Tianjin, which shows good prediction performance for both the sub-models and the overall load model. The suggested technique can accurately forecast the thermal load from the internal and external disturbance production process. Compared to the standard data-driven model, Zhao et al. discovered that the AI-driven model incorporating building thermal load characteristics achieves much greater accuracy [22]. A comparison of various AI models with advantages and limitations is given in Table 1.

LuongDuc Long [24] proposed machine learning algorithms for predicting and optimizing energy-efficient building envelopes. The recently created model comprises three primary parts: simulation, prediction, and optimization. The simulation considers a range of values for the envelope’s characteristics to replicate the building’s energy performance. The prediction model uses the Random Forest (RF), Artificial Neural Network (ANN), Deep Neural Network (DNN), Support Vector Machine (SVM), Generalized Linear Model (GENLIN), and Gradient Boosting (GB) machine learning algorithms. The results demonstrate cost and energy reductions coinciding, with 7.52 % cost savings and 8.48 % energy savings, or 21.17 % cost savings and 0.4 % energy savings, for a case study in Vietnam. This model lays the groundwork for future iterations that may include additional objectives by outlining potential design options for users to evaluate.

Danish and Senjyu [25] presented an AI-driven policy framework that aligns with the circular economy. A business plan for addressing a transition pattern in the evolution of energy policy should be implemented using a multidisciplinary procedure. The research identifies important tendencies in different methods and assesses the capabilities of AI to tackle the obstacles. To use AI’s capabilities, the AI-driven policy paradigm lays out a thorough framework and road map that considers the nature of the circular economy and how the world is changing fast. Researchers, governments, and other stakeholders may use the suggested innovative framework as a guide to understand the energy landscape of the future and capitalize on AI’s capabilities for a sustainable energy future.

Bibri et al. [26] suggested an Artificial Intelligence of Things (AIoT) for synergizing smarter eco-city brain, metabolism, and platform: Pioneering data-driven environmental governance. This research utilizes configurative and aggregative synthesis methods by conducting a thorough literature survey and in-depth analysis of various publications. This research details the technological components that make up the architecture of AIoT in smarter eco-cities and analyzes essential drivers that are pushing the development of AI and the Internet of Things into AIoT. Examining City Brain, SUM, and platform urbanism through the perspectives of artificial intelligence (AI), the Internet of things (IoT), and environmental governance (EG) uncover their shared and unique features. These data-driven solutions use real-time data analytics, predictive modeling, and stakeholder interaction to improve environmental management in smarter eco-cities.

Binyamin et al. [27] discussed Artificial intelligence-powered energy community management for developing renewable energy systems in smart homes. This study focuses on peer-to-peer (P2P) energy trading, which examines its function in the system’s functioning. Multiple case studies are reviewed, each with a different prosumer model equipped with a distinct energy storage system, solar system, and responsive demand technology, such as an electric vehicle (EV). Energy trading amounts across individuals and periods are investigated in the study using several domestic models and optimization methods.

AhsanWaqar [28] presented artificial intelligence and machine learning approaches for Intelligent decision support systems in construction engineering. Improved decision-making and project optimization are both possible with the help of these solutions. However, to fill the current research gap, it is crucial to do an exhaustive and comprehensive analysis that considers and assesses the many approaches used in this field. Intelligent DSS’s use of AI and ML approaches allows it to efficiently address various challenges, including project delays, cost overruns, and safety concerns. Intelligent DSS’s use of AI and ML approaches will enable it to efficiently

Table 1
Comparison between various AI techniques used in BMS.

Methods	Advantages	Limitations
BIM-AI Integration	Enhances smart construction management	Requires skilled workforce for execution
IoT Based Sensors	Maximizes uptime, enhances safety procedures	Relies on reliable network connectivity
ML-Based Tools	Supports performance-driven design	Dependency on quality of input data
Deep Learning Methods	Offers novel viewpoint on DL applications	Computational resource-intensive
Big Data (BD)	Enables smart and energy-conscious buildings	Data privacy and security concerns
Supply Chain Management	Enhances supply chain resilience	Integration challenges with legacy systems
Fuzzy Neural Network (FNN)	Accurate thermal load forecasting	Complexity in model tuning and training

address multiple challenges, including project delays, cost overruns, and safety concerns.

Oliveira et al. [29] suggested a synergistic potential of I4.0 technologies to drive the transition towards sustainable business models. Industries that value social responsibility, employee well-being, and stakeholder involvement are fostered, and ethical dimensions are shaped by organizational social practices, which are also explored. This study's results have policy, academic, and business ramifications. Practitioners and policymakers will acquire practical insights for promoting socially responsible and environmentally sensitive initiatives inside Multinational Enterprises (MNEs). At the same time, scholars will grasp the complex dynamics influencing sustainable practices within the I4.0 framework.

Aven Satre-Meloy et al. [30] discussed Reducing the cost of home energy upgrades in the US. The study gathered data on the expected cost reduction potential and probability of application of these tactics in the construction sector using quantitative and qualitative questions. People with expertise in implementing energy improvements in US single-family and multi-family buildings comprised 167 survey respondents. They included architects, contractors, energy consultants, and manufacturers. This research shows that the solutions might significantly improve the customer economics of a typical deep retrofit project by reducing the total installed cost by around 50 %.

AlirezaNorouziasas et al. [31] deliberated the Impact of space utilization and work time flexibility on the energy performance of office buildings. Using IDA ICE 5.0, this research developed and evaluated ten distinct occupancy scheduling scenarios based on flexible arrangements, ranging from traditional workweeks to extended remote work arrangements. According to the results, increasing telework and decreasing work weeks both substantially decrease energy use. An example of how occupancy-based techniques may improve building energy efficiency is the 23 % drop in electric heating demand that followed the introduction of flexible hours and remote work in situations. Nonetheless, the unpleasant hours rose by 59 % in the 2-day remote working scenario compared to the basic case, showing that weather conditions should be considered when adopting remote work.

TianfeiGao et al. [32] suggested an integrated approach to predicting heating and cooling loads using machine learning and optimization algorithms to enhance building energy efficiency. Using a dataset of 768 samples, this work utilizes machine learning algorithms that include Support Vector Regression, Extreme Gradient Boosting, and an ensemble model based on Dempster-Shafer Theory. R2, RMSE, n10-index, MARE, SI, WAPE, and NSE are some evaluation measures that measure how well a model acts. When it comes to predicting HVAC loads, XGB is superior to SVR. With an RMSE of 0.9729 and R2 of 99.17 % for the heating load estimate, the XGSH model achieves the best performance. This model combines XGB with the Sea-Horse Optimizer. Similarly, the XGSH model trains with the best cooling load estimate results (99.36 %) and the lowest root-mean-square error (0.7723).

Helena Kuivjõgi et al. [33] recommended the Data-driven baseline generation for post-retrofit energy saving assessment, a statistical and machine learning method comparison. This research evaluated two approaches to estimating future heating and electrical energy use as a starting point for post-retrofit assessment. The ASHRAE Guidelines for yearly energy usage do not allow an upper error margin of CVRMSE 25 %. When validated with simulated data, heating, and electricity models employing the degree-day technique had an actual error ranging from 4.5 % to 10.4 %, whereas machine learning models had an uncertainty ranging from 1.4 % to 7.5 %. Machine learning models had an uncertainty of 6.11%–17.5 % when applied to metered data, but the degree-day technique displayed an uncertainty of 8.4–19.3 %.

Based on the survey, there are several issues with existing models in attaining a high-performance ratio, community involvement ratio, economic growth ratio, Sustainability ratio, and resilience ratio. Hence, this paper proposes the Integrated AI-Driven Smart Buildings Framework (IAI-DSBF) to manage smart buildings' monetary, societal, policy, and regulatory components powered by artificial intelligence.

The main objectives of this research are as follows:

- ✓ IAI-DSBF has significant potential to improve the quality and performance and overcome many of the challenges confronted by urban areas.
- ✓ It addresses the critical need to consider the wider economic, social, and regulatory aspects of smart buildings powered by artificial intelligence.
- ✓ IAI-DSBF in smart cities, particularly about building performances and urban planning, encourages the community's welfare.

2. Proposed method

Through the seamless integration of state-of-the-art AI technology with public policy, social inclusion, and financial planning, the IAI-DSBF transforms city planning. AI guarantees optimal resource usage by improving the efficiency and effectiveness of building operations. Aligning policies promotes equity and inclusion, while solutions for economic management provide long-term financial sustainability. Energy management techniques and the incorporation of public health are given precedence over resilience and sustainability. In times of crisis, it becomes much easier to respond quickly, protecting people and property. Better building performance, compliance with regulations, community involvement, and sustainability are the results of IAI-DSBF, which pave the way for future-ready, flexible communities. All these plans will lead to a more fair and equal society.

An all-encompassing method for metropolis planning is offered by using the IAI-DSBF, which integrates ultra-modern AI with monetary planning, public policy, and social inclusion. Fundamentally, the AI era increases the effectiveness and performance of constructing operations, making higher use of available assets. Efficient and lengthy-term monetary viability is assured via financial control solutions. Parts of guidelines and rules ensure the entirety is consistent with what society requires, which allows for the promotion of equality and inclusion. This paradigm goes beyond the best buildings; it affects choices in urban planning and supplies groups that might be welcoming to anyone. Sustainability and accelerated resistance to environmental stresses are two desires of energy control strategies. Incorporating public health principles also improves the health of the community. The framework allows for efficient and rapid action during emergencies, including natural catastrophes, protecting people and infrastructure. Better building performance, compliance with regulations, community involvement, and sustainability are the results of IAI-DSBF.

This framework establishes the basis for future-ready, adaptable cities by emphasizing inclusion and resilience, as shown in Fig. 1.

$$\min_{\forall_1} F_{bj\sim b_{-j},\sim\propto_{-j},} t' > Q\left[\sum_{u=1}^{I} \forall^u \times s_{j,u} + v_{j,o}|\partial\right] = v_{j,u} - v_{j,u-1} \tag{1}$$

The policy limitations (α), social consequences (∀), and economic benefits (b_j) are all elements that Equation (1) takes into account. To achieve harmony and improvement in AI-driven smart buildings, the IAI-DSBF framework uses this optimization. Denoting the aggregate benefits and restrictions over multiple situations (u), the term $\forall^u \times s_{j,u} + v_{j,o}|\partial$ ensures that the incremental utility $v_{j,u} - v_{j,u-1}$ matches with societal and regulatory objectives.

$$v_{j,u} = \frac{D_{j,u}^{1-\forall}}{1-\partial} - M_{j,t}, 1, \forall \ < 0, (m + qt) + (r + qw) \tag{2}$$

Equation (2) for the utility of a smart building element (j) under various use situations (u) is given by $\frac{D_{j,u}^{1-\forall}}{1-\partial}$, where D is the demand and $\forall$ and ∂ are the effectiveness parameters. In this case, ongoing costs over time (t) are denoted by $M_{j,t}$, while the extra operational and regulatory expenses are captured by $(m + qt) + (r + qw)$.

$$\min_{\forall_1} F_{ck\sim z,\sim D\propto_{-vj},} ep' > R\left[\sum_{t=1}^{I} kQ^{wu} \times Tv_{bj,ru} + De_{j,ko}|\Delta\partial\right] = Wp_{wj,qu} - rv_{jf,p-1} \tag{3}$$

Several components, including cost (ck), desire (D), and efficiency characteristics ($D\propto_{-vj}$), are included in the optimization issue that Equation (3) aims to minimize. Taken together, operational advantages (kQ^{wu}) and prior performance ($Tv_{bj,ru} + De_{j,ko}$) constitute,

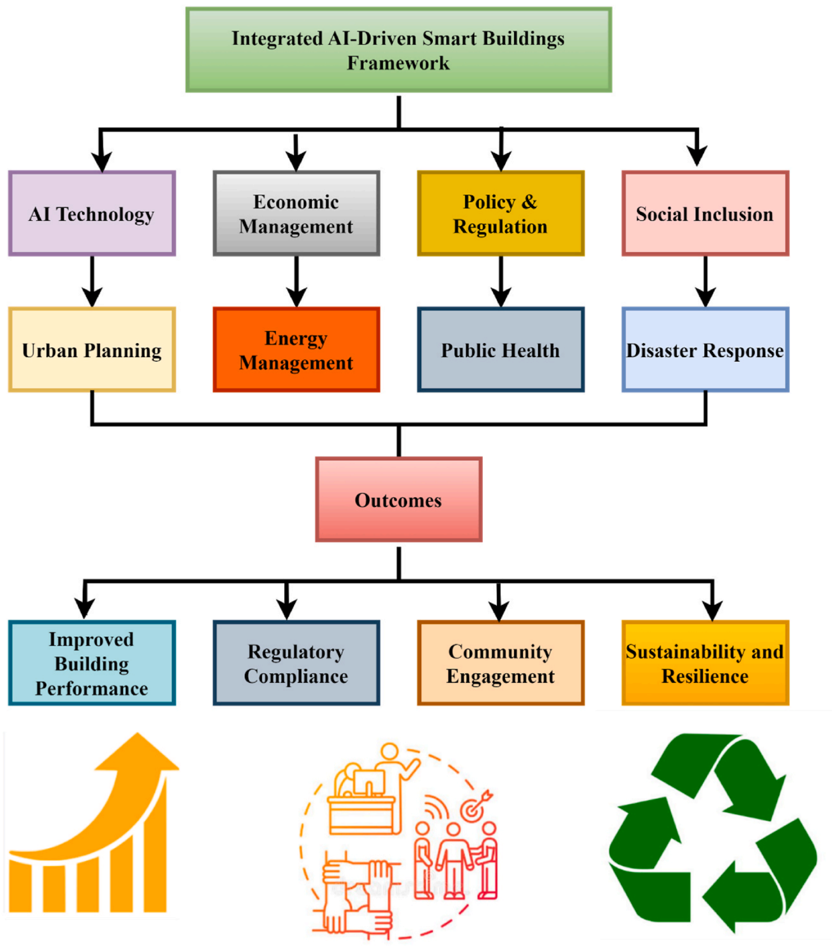

Fig. 1. Block diagram of IAI-DSBF.

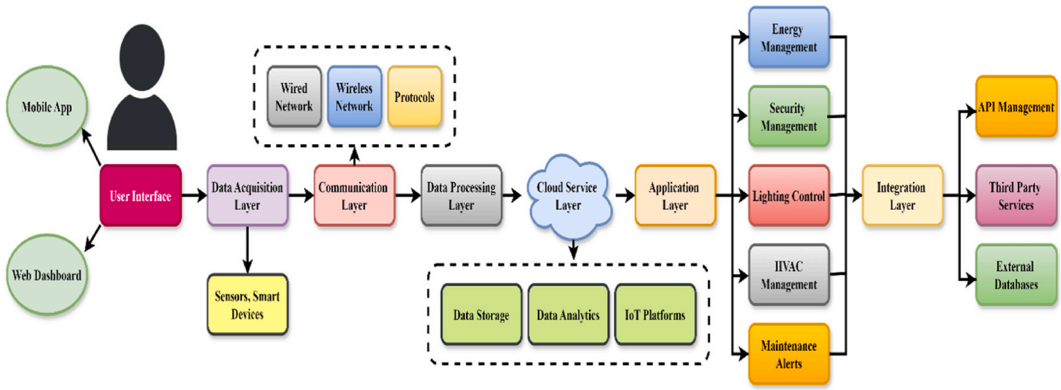

Fig. 2. Smart buildings using data acquisition and cloud services.

which reflects the net performance.

2.1. Smart Buildings Using Data Acquisition and Cloud Services

This system's user interface layer accommodates a wide range of user preferences by making the system accessible via online dashboards and mobile apps. The data acquisition layer is located below it. Here, smart devices, sensors, and building management systems gather a wealth of data, such as motion, humidity, and temperature, to provide a thorough picture of the building's environment. Wi-Fi, Zigbee, and Z-Wave are just a few of the protocols used by the communication layer to guarantee smooth connection across wired and wireless networks. Before transmission to the cloud services layer, data undergoes preprocessing at the data processing layer via edge computing and gateways. Advanced insights and decision-making are made possible at the cloud services layer via data storage, analytics, and AI/ML models. Energy, security, HVAC, lighting, occupancy, and maintenance management are all handled by the application layer, which uses these features. Fig. 2, ensuring interoperability and scalability, the integration layer harmonizes the whole system by handling third-party services, external databases, and APIs. Building operations are optimized, user experiences are enhanced, and sustainable, intelligent environments are fostered by this complete design.

$$U(a) = \sum_{k=1}^{C} \partial_k \times \left((c_{k+1} - c_k)1\ [a > c_{k+1}] + (a - c_k)1\ [c_k < a < b_{k+1}] \right. \tag{4}$$

Using periods $c_{k+1} - c_k$ with weights $U(a)$ Equation (4) represents the utility $U(a)$ of an action a. The utility can only be estimated within certain ranges, as guaranteed by the indicator function $c_k < a < b_{k+1}$.

$$v_{j,u} = \frac{D_{j,u}^{1-\partial} - 1}{1 - \forall} - Q_{j,k}(m-k) \times (1 - 2p) \tag{5}$$

The value of a smart building component $v_{j,u}$ may be expressed using Equation (5). The term $D_{j,u}^{1-\partial} - 1$ represents the adjusted demand $Q_{j,k}$ according to the efficiency parameters $1 - \forall$ and $1 - 2p$.

$$\min_{A_j} F_{b1\sim Q_1,\ldots,} b_{p\sim r_k}, d_f \left[\sum_{u=0}^{I} \forall^u s_p \right] + (1 - st) \tag{6}$$

Minimizing a function $F_{b1\sim Q_1,\ldots,}$ across a collection of actions A_j is the goal of the optimization problem stated by the equation. This function considers different advantages and limitations denoted by $b_{p\sim r_k,}$ and $\forall^u s_p$. An extra element that could indicate system stability or another performance measure is included in the weighted effects $1 - st$ across various situations. Algorithm 1 shows the energy consumption modeling of smart buildings.

Algorithm 1. Energy Consumption Model in Smart Buildings

Input: User Activity Patterns
Output: Probability of power consumption

Update the transition matrix for every user
Calculate the transition matrix for every user
While $t \in$ *peak hours duration*
For each user, **do**
end for
update $t++$

(*continued on next page*)

(*continued*)

end while
Compute the average probability of every combination over all timeslots, considering the probabilities
Using the average probabilities, measure the probability of power consumption at every level
return

2.2. Flow Diagram of Smart Buildings Policy, social, and regulatory aspects

It is critical to recognize these gaps as a first step in tackling socioeconomic inequities to keep sensitive information secure, and strong data privacy safeguards must always be put in place. It is crucial to navigate regulatory frameworks to maintain compliance and ethical standards. Encouraging diversity requires equal access to smart technology. Better use of sources and extra performance are two consequences of incorporating AI technology into building management. Long-term fulfillment requires careful fiscal, social, policy, and regulatory control. A multipronged strategy, which includes capable policymaking, is necessary to acquire financial development. Ensuring underprivileged populations get the blessings of era development calls for actively promoting social inclusion. To effectively traverse ever-converting criminal frameworks, one has to master the artwork of negotiating complex guidelines. The eventual goal is to make society fairer and extra-positioned and cease discrepancies. To go down this path, one must persistently seek out information on the causes of socioeconomic inequality and ways to alleviate it. Smart buildings can get closer to an equitable society where everyone can work together and take a holistic approach, as shown in Fig. 3.

The variables and their effects on a certain set J_k are shown in Equation (7). In this case, F is a function that takes into consideration a range of factors, including $b1$, r_f, and $P_w \sim Q$. The effects of these factors across different scenarios are aggregated in the summary term $\tau^{\sigma-1}$ and $\beta_z(c_{jk}|d_{vb})$ represent specific coefficients.

$$\forall J_k \mp F_{b1\sim r_f}, \dots, c_{f\sim P_w\sim Q}\left[\sum_{u=0}^{I}\tau^{\sigma-1}, \log \beta_z\left(c_{jk}\middle|d_{vb}\right)\right] \tag{7}$$

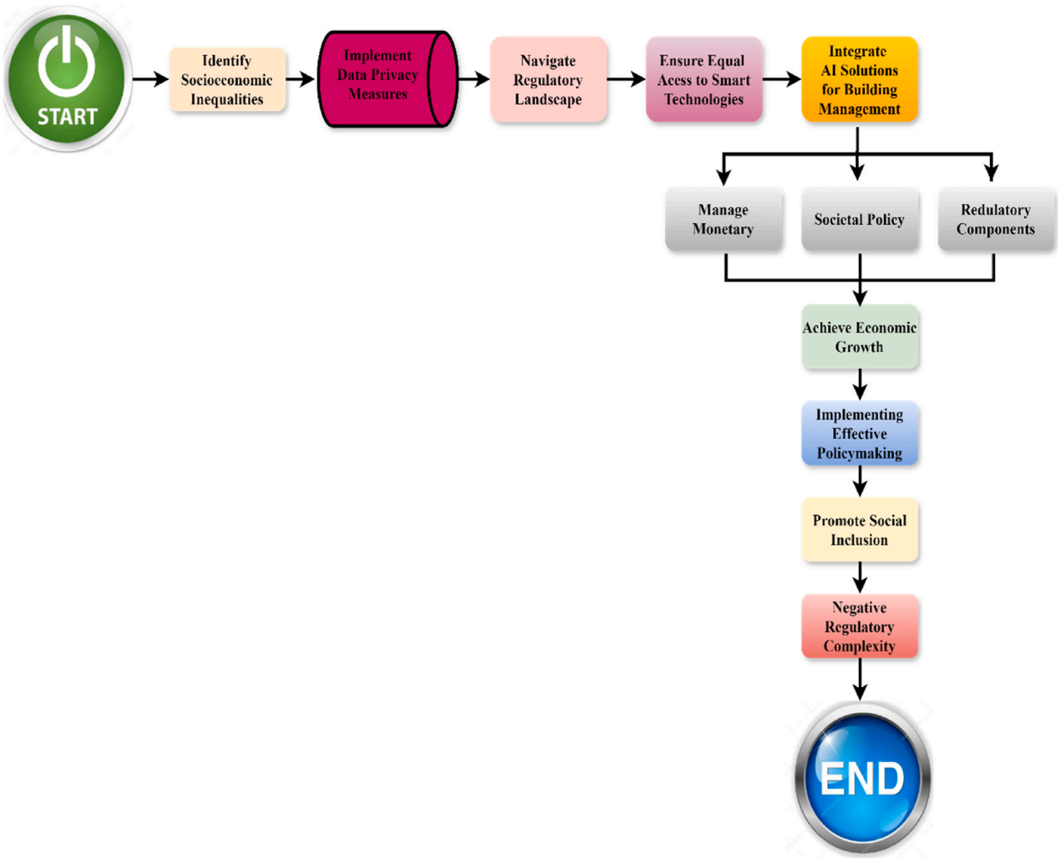

Fig. 3. Flow diagram of smart buildings policy, social, and regulatory aspects.

$$\partial_k : \min_{\partial_k} F_{\forall-\propto_q}\left[\sum_{u=1}^{L} \propto_{j+w} + q_p + w\right], (p+1) = 0 \tag{8}$$

Here, $F_{\forall-\propto_q}$ are factors that affect the function, and the goal of the optimization problem is to minimize the function ∂_k on Equation (8). In various circumstances $\propto_{j+w}$, the combination term $q_p + w$ brings together the combined effects of extra factors $p+\ 1$.

$$fg\,(D_u) = 1 - \frac{P}{P-1}\,hjpj\,(D_u), 0 > fw\,(D_u) > 1 \tag{9}$$

Equation (9) illustrates a connection in which the function $fg\,(D_u)$ is dependent on the demand D_u, with the term $1-\frac{P}{P-1}$ serving as an adjustment. In this context, P denotes a parameter that affects the modification, and $hjpj\,(D_u)$ stands for an additional demand function. Restricting another function $fw\,(D_u)$ to a specified range is indicated by the condition.

2.3. Controlling and Managing Smart Building

One example of a proactive strategy towards renewable energy is the integration of wind turbines and photovoltaic (PV) modules into smart buildings. Installed on roofs or facades, PV modules collect sunlight, transform it into electricity, and add to the building's power needs. Their low maintenance needs and whisper-quiet operation make them perfect for smart building integration. When installed in optimal locations, wind turbines harness the wind's kinetic energy and turn it into useable electricity. In regions with abundant wind, they may supplement PV modules as a sustainable energy source. Fig. 4 shows all these renewable energy sources work together to lessen our impact on the environment by cutting down on emissions of greenhouse gases and our dependency on fossil

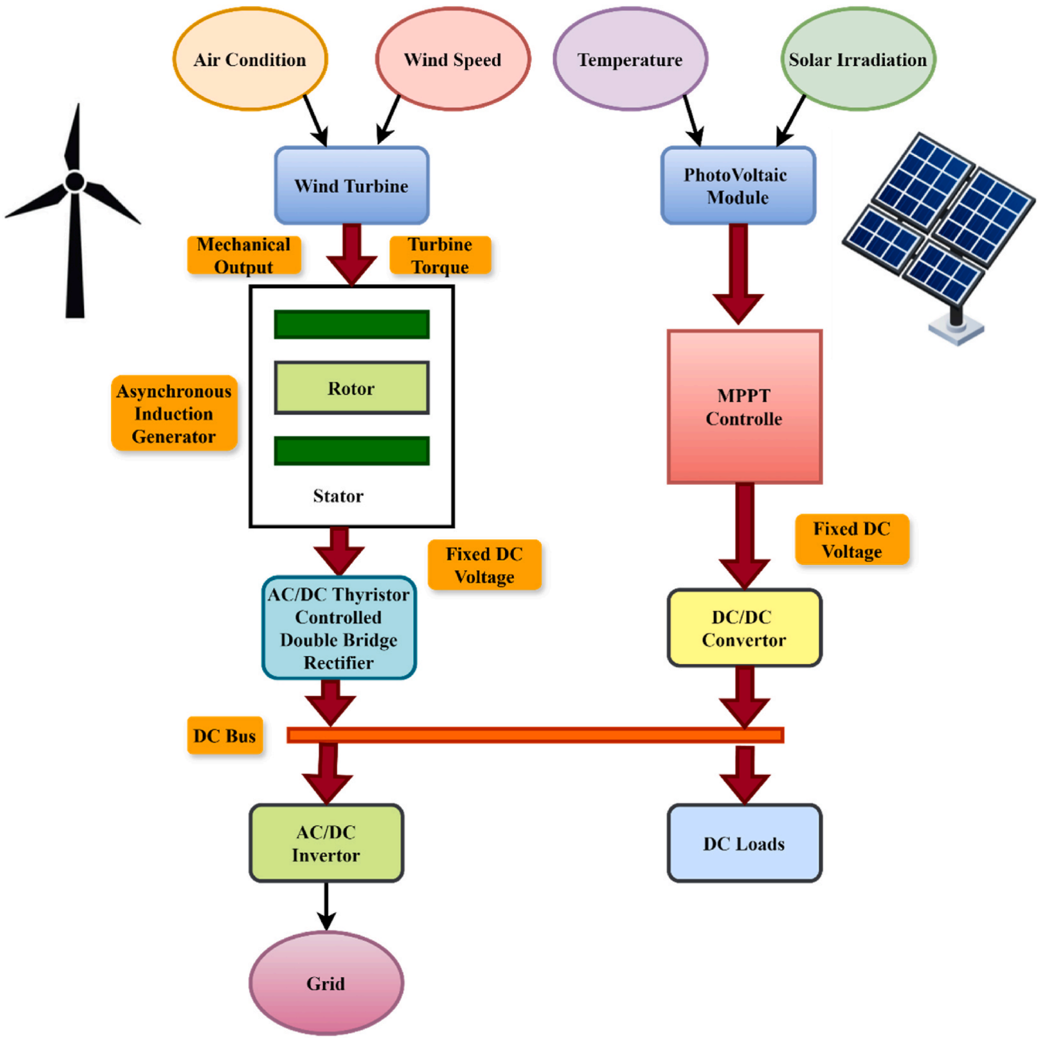

Fig. 4. Controlling and managing smart building.

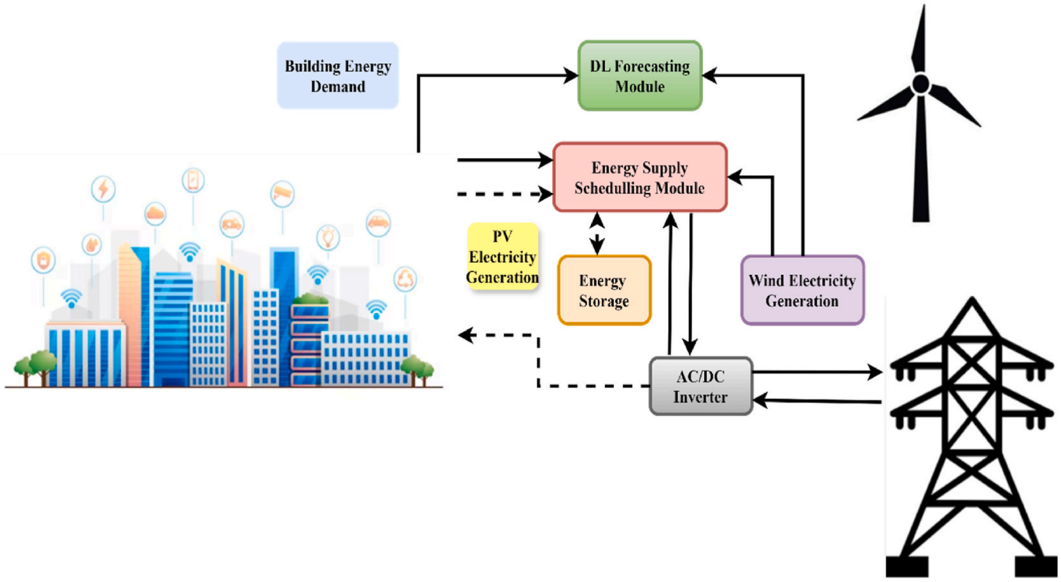

Fig. 5. An integrated smart active Building's schematic using renewable energy sources.

fuels. Smart buildings may improve energy production and consumption by connecting these systems to modern monitoring and control systems. This further enhances efficiency and sustainability. Organizations may showcase their dedication to environmental responsibility and enjoy the advantages of clean, renewable energy by integrating PV modules and wind turbines into smart building infrastructures.

$$hjpj\ (D_u) = \frac{\sum_{j=2}^{P} \sum_{k=1}^{Q} \left(D_{j,u} - E^{k,p}\right)}{2\,P \sum_{j=1}^{P} D_{k,p}}, 0 > hjpj\ (D_u) + \frac{P}{P-1} \tag{10}$$

A standardized measure of demand, D_u, adjusted by deviations from an anticipated value, *hjpj*, is defined by the equation as 10, the resultant value is averaged, and the summations continue over different indices $D_{j,u} - E^{k,p}$. The function remains inside a given range because of the restriction $\frac{P}{P-1}$.

$$qspe\ (D_u) = \sum_{j}^{v} E_{j,p} + (u-1) + (km + t) \tag{11}$$

The analysis improved the performance ratio, denoted by Equation (11), $qspe\ (D_u)$, is the result of adding up the several elements that lead to better performance. All of the terms in the total, including $E_{j,p}$, and $(km + t)$, stand for distinct elements, such as initial performance, effects over time, and extra improvements.

$$txq_p = \sum_{j=1}^{P} \partial_k \times v_{l,q}\left(txq_p\right) = fh\ (D_u) \times srd\ (D_u) \tag{12}$$

The variable txq_p is calculated by taking the analysis of community involvement ∂_k and a value $v_{l,q}$ in Equation (12). Furthermore, the function $fh\ (D_u)$ and the function $srd\ (D_u)$ are used to indicate community engagement in improving the building's performance. Algorithm 2 shows the IoTpseudocode for energy control in air conditioners.

Algorithm 2. The Internet of Things Pseudocode for Energy Control in Air Conditioners

Capture the image with the camera
Resize the image
Input the image data into the FNNmodel
Do the recognition progression by the FNN
Publish the number of identified individuals by message queuing telemetry transport protocol
Do data analysis by Interactioncomponents for IoT
if the number of individuals ≥ 1
Send signal "1" by message queuing telemetry transport protocol to the AC microcontroller.
Link the power of the air conditioner

(continued on next page)

(*continued*)

Present the number of individuals on the IoT dashboard
Record the event of AC "ON"
else
Send signal "0" by message queuing telemetry transport protocol to the AC microcontroller
Cut off the power of the AC
Present the number of individuals on the IoT dashboards
Record the event or turn OFF the AC
end if
Record all events and data on the system database for further analysis.

2.4. An Integrated Smart Active Building's Schematic Using Renewable Energy Sources

The idea of a smart integrated energy management system is shown in Fig. 5. To maximize the energy supply package, a clever integrated energy system schedules different energy supply resources that are renewable and non-renewable energy sources. An energy system continually compares energy supply and demand levels to reduce the amount of energy supplied by non-renewable energy sources. Energy management in smart active buildings requires detailed data sets on energy output and consumption, such as hourly or half-hourly statistics, to allow smart integrated energy systems. Moreover, there is a great deal of complexity and non-linearity in the energy modeling of the smart building that uses RE sources. Since meteorological data is erratic, there is unpredictability in the patterns of energy output throughout the day and seasons, all of which are factors in renewable energy. Appliance scheduling is the primary focus of home energy management systems scheduling techniques, which aim to reduce energy expenses. The efficiency of active building management systems may be greatly increased by forecasting algorithms that predict energy production and consumption in buildings, as shown in Fig. 5.

$$fph\ (\forall) = -F_{b+q}\left[\log\forall\left(b|v_p : \partial_k\right)\right] \tag{13}$$

The function $fph\ (\forall)$ that analysis of economic growth, which $\forall$ signifies economic elements, is given by Equation (13). The term captures the effect of different economic variables F_{b+q}, and the logarithmic connection between economic factors and the impact have on construction efficiency is represented by $\log\forall\left(b|v_p : \partial_k\right)$.

$$V_{(a)} = \frac{1 - H(a)}{1 - H\ (a) + b(a)f(a)} \times \frac{a.\ g(a)}{1 - A(z)} \tag{14}$$

One way to measure the analysis of the sustainability ratio $V_{(a)}$ This is done by looking at the sustainability ratio defined by Equation (14). Factors such as the functional $H(a)$ and $b(a)f(a)$ changes the numerator, which indicates the importance of a to long-term viability, while the $A(z)$ reflects limitations.

$$H(a) = \frac{1}{1 - G(a)} \int_{a=a}^{\forall} C(z^p)h\ (a_k) + eak \tag{15}$$

To measure analysis of resilience $H(a)$ can endure and bounce back from shocks or disruptions, the resilience metric $G(a)$ is defined by Equation (15). Over a range from a particular point to the system's full capacity, the aggregate effect of components like external circumstances $C(z^p)h$, system responses capacity to adapt eak is represented by the integral term. Algorithm 3 shows the rule-based building energy management model.

Algorithm 3. Rule-based Building Energy Management Model.

Procedure rule-based (control, time, sensor)
    System Initialization
    Read Sensors
    Read thermal comfort constraints
    If valid sensors = true, **then**
    If $(15:00) \leq 17:00)$
    Pre-peak or off-peak
    Set the control heating systems ON to charge thermal energy storage
    Else if $(17:00) \leq 19:00)$
    Set the control heating systems OFF **End if**
    Else
    Set the control heating systems ON **End if**
    End procedure

In summary, by combining cutting-edge AI with public policy, social inclusion, and financial planning, the IAI-DSBF completely changes the game regarding city planning. By maximizing available resources, AI improves the efficacy and efficiency of building operations. Economic management guarantees long-term financial sustainability, while policy alignment promotes fairness and inclusion. Resilience and sustainability are improved by making public health and energy management priorities. Protecting lives and property during emergencies is easier with the ability to respond quickly. By enhancing building performance, ensuring regulatory compliance, fostering community engagement, and promoting sustainability, IAI-DSBF paves the path for future-ready and adaptable communities. All these things add up to make our society more equitable, making our future better for everyone.

3. Result and discussion

Disadvantages and advantages of incorporating artificial intelligence into building management systems have been provided by improving building operations. IAI-DSBF provides a step-by-step approach to enhancing productivity, environmental friendliness, and occupant convenience. It is important for several reasons, such as removing legislative barriers, resolving socioeconomic disparities, and ensuring everyone can access smart technology. This study evaluates to what extent the IAI-DSBF achieves these objectives and improves building performance.

Utilizing the framework's quantitative indicators, building managers may make data-driven choices to modify heating, lighting, and ventilation according to real-time occupancy patterns, decreasing energy expenses and carbon emissions. Furthermore, the IAI-DSBF directs adherence to regulatory requirements, guaranteeing that buildings enhance performance and comply with safety, privacy, and environmental rules. The framework enhances occupant well-being by integrating user choices and health data, resulting in more intelligent and adaptable building environment. The framework facilitates the seamless integration of AI-driven technologies that enhance building functionality and sustainability while adhering to economic and regulatory objectives.

The testing was in a fully functional smart building controlled by AI. The building had Internet of Things (IoT) sensors that tracked temperature, humidity, occupancy, lighting, and energy use. To offer high-resolution, real-time insights into operational and environmental conditions, these sensors collected data at 10-s intervals. To ensure the safety and integrity of the data, the processing was done on a high-performance server located behind a secure private network. The server included an Intel Xeon CPU and 128 GB of RAM. Data was preprocessed to guarantee precision and uniformity by removing outliers and normalizing the data. Various criteria, like occupancy levels and time of day, were recorded to evaluate the AI system's efficacy. This allowed for an exhaustive assessment of system performance in various conditions.

Dataset Description: The data are taken from the smart-building system Kaggle dataset [23]. Each room contains five types of measurements: Passive Infrared Sensor (PIS) motion sensor, temperature sensor, luminance level sensor, air humidity sensor, and CO_2 concentration sensor. The present research data is collected for one week from Friday, August 23, 2024, to Saturday, August 31, 2024. The PIS motion sensor is sampled every 10 s, while other sensors are sampled every 5 s. Each file shows sensor readings alongside timestamps on the Unix epoch time scale. PIS sensor detects infrared light emitted by objects within its field-of-view, which determines room occupancy, i.e., how many occupants are present there. Approximately 6 % of the PIS data have non-zero values, meaning that the room is occupied, while null PIR data means otherwise.

3.1. IAI-DSBF performance analysis

The effectiveness of the IAI-DSBF in improving the performance of building operations compared to other approaches is depicted in Fig. 6. Efficiency, sustainability, and occupant consolation are significantly stronger when AI technology is integrated into construction management systems. The framework systematically deals with statistics privateness, regulatory hurdles, and socioeconomic inequality to ensure everybody can access the smart era. The IAI-DSBF performance output is 99.1 %, with an 80th sample. The analysis of an improved performance of 99.1 % was accomplished within the proposed method, as shown in Fig. 6. At sampling 80, the performance has increased by around 6.68 % compared to the 100 samples of other approaches. For IAI-DSBF, the performance is

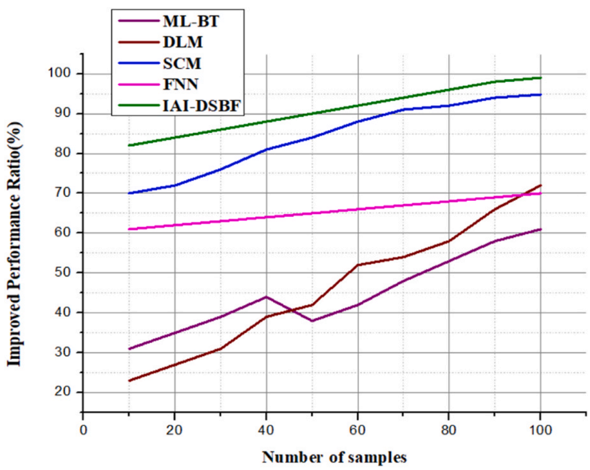

Fig. 6. Comparison of IAI-DSBF performance with other approaches.

about 82 % (minimum) to 99 % (maximum). This indicates its robustness in the accuracy analysis and effectiveness in intelligence judgment compared to other approaches. The IAI-DSBF promotes inclusive society, effective policymaking, and monetary progress by managing all four economic, social, policy, and law additives. It promotes transparency, accountability, and social welfare while navigating complicated regulatory landscapes and inspiring community engagement. The technique has been proven to beautify building general performance signs and regulatory compliance while encouraging network involvement in keeping with the simulation findings. As this research suggests, integrating AI-driven smart homes is critical to considering massive financial, social, and regulatory worries. Building inclusive, sustainable, and resilient towns requires an integrated method that uses aintelligent era. The proposed IAI-DSBF approach will facilitate precise metrics for energy savings, operational efficiency, cost-benefit analysis, and clear policy and social impact assessments. The IAI-DSBF framework thus provides a balanced view that outlines the advantages and challenges of these technologies and quantifies their effectiveness, making it easier for stakeholders to make informed decisions based on reliable performance data and regulatory compliance.

3.2. IAI-DSBF's community involvement analysis

Improved building performance and more community involvement are two outcomes of the framework's use of artificial intelligence in building management systems. Communities are given the ability to actively engage in smart building initiative decision-making via the IAI-DSBF. Workshops where participants work together, community forums, and feedback sessions are all examples of ways people might become involved. The framework ensures that smart building initiatives align with community needs and objectives by including local companies, residents, and stakeholders in the design and implementation phases. When the community is involved, smart building efforts are more likely to be open, accountable, and trustworthy. It builds community ownership by getting people talking about the pros and cons of AI-driven technology in their areas and raising their understanding of these issues. Research on community engagement shows that stakeholders should be included in making smart city plans so that cities may be more inclusive, sustainable, and resilient. TheIAI-DSBFcommunity involvement is 98.5 %, with 80 samples. The analysis of an improved community involvement of 98.5 % accomplished within the proposed method is shown in Fig. 7. At several80 samples, the community involvement has increased by around 7.72 % compared to the 100 samples. The community involvement in the smart building is about 98.5 %.AI-driven smart buildings are revolutionizing sustainable building practices with enhanced energy efficiency, robust security measures, and automated facility management technologies.

3.3. Analysis of economic growth using IAI-DSBF

Analysis of economic growth using IAI-DSBF and other approaches is illustrated in Fig. 8. Incorporating AI into various aspects of building management systems like resource usage optimization and operational cost reduction coupled with effectiveness increase gives room for efficiency in resource usage by developing an artificial intelligence-driven design platform for urban areas, which contributes directly to improving one's life quality". Here are a few direct and indirect economic benefits associated with IAI-DSBF utilization. New digital vacancies have enormous potential (e.g., data analysis firms or organizations that provide technical maintenance services at intelligent buildings). Given their increased efficiencies and productivity levels compared to traditional commercial premises, businesses are attracted to smart building investments that attract investment and economic activities within metropolitan areas. The IAI-DSBFeconomic growth is 99.12 % with an 80 number of samples. The analysis of an improved economic growth of 99.12 % accomplished within the proposed method is shown in Fig. 8. At several80 samples, the economic growth has increased by around 6.62 % compared to the 100 samples. For smart buildings, the economic ratio is in the range of 99.12 %. Innovation and entrepreneurship are encouraged by the IAI-DSBF as a way of supporting technological advancement and business expansion. To enhance private sector investment in smart building projects, there must be efficient legislative and regulatory frameworks, which in turn contribute to economic growth. The findings illustrate that the IAI-DSBF is crucial for increasing economic activity, generating employment opportunities, and promoting new approaches to city planning. It is, therefore, possible for cities to tap into their

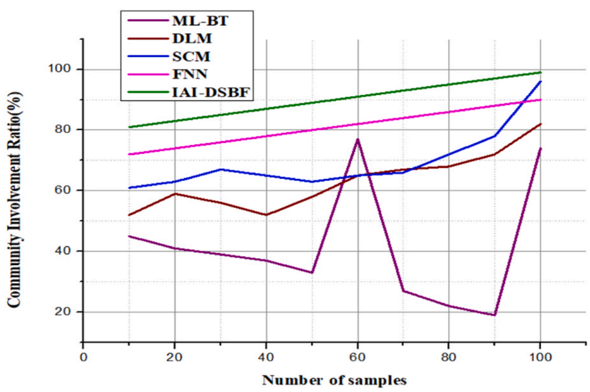

Fig. 7. Comparison of Community Involvement for IAI-DSBF with other approaches.

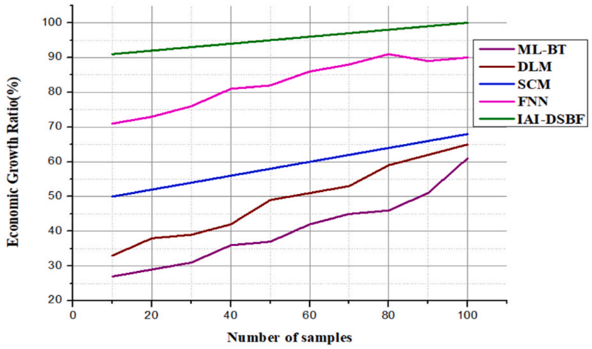

Fig. 8. Analysis of Economic Growth using IAI-DSBF and other approaches.

economic potential, thereby creating sustainable communities using AI-driven technology.

3.4. Sustainability analysis using IAI-DSBF

The analysis of sustainability using IAI-DSBF and other approaches is depicted in Fig. 9. Examining sustainability through the lens of the IAI-DSBF brings interest to its function in encouraging ecological duty and flexibility. The framework decreases strength consumption, maximizes resource utilization, and minimizes environmental effects by integrating AI into building management structures. Efficiency in strength use, waste discount, and carbon footprint reduction are all parts of the IAI-DSBF's sustainability plan. Smart buildings that are part of the framework can lessen their energy consumption and carbon emissions due to optimization algorithms powered through artificial intelligence and sophisticated statistics analytics. The IAI-DSBF Sustainability ratio is 98.2 % with an 80 Number of samples. The analysis of an improved Sustainability ratio of 98.2 % accomplished within the proposed method is shown in Fig. 9. At several80 samples, the sustainability ratio has increased by around 5.24 % compared to 100 samples. Fig. 9 shows the sustainability ratio of 98.2 % in the smart building. The IAI-DSBF additionally encourages the use of sun and wind strength, among other renewables, in constructing operations to reduce the impact on the surroundings and fossil fuel use. Resilience in the face of environmental challenges and the consequences of weather alternates are also highlighted in the framework. Smart buildings are extra resilient and can improve faster from calamities because they consist of adaptive strategies and disaster response approaches. The studies highlight the importance of the IAI-DSBF in achieving sustainability targets, encouraging environmental obligation, and constructing future-proof societies.

3.5. Resilience analysis using IAI-DSBF

The resilience analysis for IAI-DSBF and other approaches is depicted in Fig. 10A critical thing of resilience analysis within the IAI-DSBF is the capacity to bear and get better from distinct types of stress. The IAI-DSBF approach improves resilience by using AI in constructing management systems to predict dangers proactively, and it puts in force adaptive solutions and speedy replies. All three aspects of bodily, social, and economic resilience are part of what the IAI-DSBF measures and takes preventive action. Using the framework's real-time monitoring and predictive analytics, clever homes can protect themselves in opposition to calamities, cyber-attacks, and infrastructure breakdowns. The IAI-DSBFresilience ratio is 97.5 % with an 80 number of samples. An improved resilience

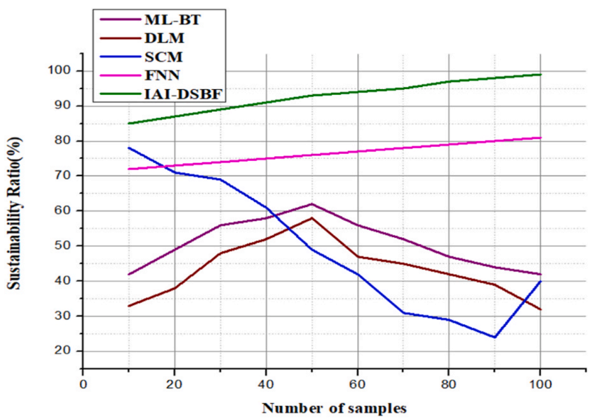

Fig. 9. Analysis of sustainability using IAI-DSBF and other approaches.

ratio of 97.5 % was analyzed within the proposed method, as observed in Fig. 10. At several80 samples, the resilience ratio has increased by around 5.72 % compared to the 100 samples. By encouraging stakeholders to paint collectively, communicate, and take collective motion, the framework also allows communities to grow extra resilient. Smart buildings are important to resilient urban ecosystems because they consist of people, groups, and government.

Regarding economics, the IAI-DSBF improves resilience by decreasing losses, retaining operations strolling for crises, and minimizing downtime. Incorporating adaptive strategies and catastrophe recovery plans lets smart buildings hastily adjust to new instances and pop out more potent on the alternative side. The evaluation highlights the cost of the IAI-DSBF in creating infrastructure and groups that can bear and get better from shocks. The IAI-DSBF encourages funding for clever construction tasks and the creation of new jobs, each of which contributes to monetary development. Addressing environmental issues and establishing resilient urban ecosystems are emphasized using the significance of financial growth. The outcomes show how critical the IAI-DSBF is for making future towns more resilient and sustainable.

Collecting data persisted a significant challenge, especially when integrating the smart building's many sensor systems. Possible inconsistencies in the acquired data resulted from the difficulty in guaranteeing compatibility and dependability among different sensors. Furthermore, changes in the outside world, including changing weather patterns or occupancy levels, might inject noise into the data, making the analysis more difficult. Secondly, there were difficulties caused by the complicated training procedures of AI systems. Spending a lot of effort and computing power fine-tuning the models was often necessary to get things to operate at their best. Although it may increase model accuracy in some instances, this procedure can be resource-intensive in alternatives.

Significant security issues for inhabitants are raised by the collecting and processing of sensitive data, including occupancy patterns, environmental conditions, and personal preferences. Implementing robust data anonymization methods and receiving informed permission from users are essential steps in managing data that complies with data protection rules like the General Data Protection Regulation (GDPR) and other local legislation. Cybercriminals have a larger target area to exploit due to the proliferation of AI systems and sensor integration. The privacy and safety of the occupants may be jeopardized if vulnerabilities in these interrelated systems allow unauthorized parties to access crucial data. Safeguarding data integrity and preserving user confidence requires robust security measures, including encryption, secure communication protocols, and frequent security audits.

Reliable environmental measurements and occupancy monitoring were expected during the testing period due to the assumption that the sensors installed throughout the smart building performed with constant precision and minimum data loss. Furthermore, it was assumed that environmental variables like weather and occupancy patterns reflected regular building use, mirroring practical operating situations. It was assumed that the server and network infrastructure resolve keep running smoothly without any significant delays or security breaches that may affect the outcomes of the AI algorithm assessment. In addition, extreme results were eliminated during data preparation on the assumption that they indicated mistakes or non-representative data points, thereby avoiding analytical distortions. The results can be more convincingly presented if they were accompanied by pictures of the sensor locations and data flow diagrams that explain how the data was processed and acquired in the controlled setting of the investigation.

4. Conclusion

Several analyses were conducted to identify the most productive researchers, organizations, or countries involved in a field of study and to identify the main details of a research topic, which is relevant given the use of AI in smart, intelligent, and green buildings. The existing bibliometric analyses in the scientific literature primarily focus on analyzing various types of modern buildings rather than the technology used to construct them. The scientific literature must fill this knowledge vacuum with a bibliometric study of smart and green buildings focusing on AI technologies. This article significantly contributes by conducting the first bibliometric analysis of AI techniques in green and smart buildings. This will help interested scholars and professionals gain a scientific overview of the field's existing research, which is a crucial endeavor. Once taught properly, AI-based prediction algorithms show great promise for accurate

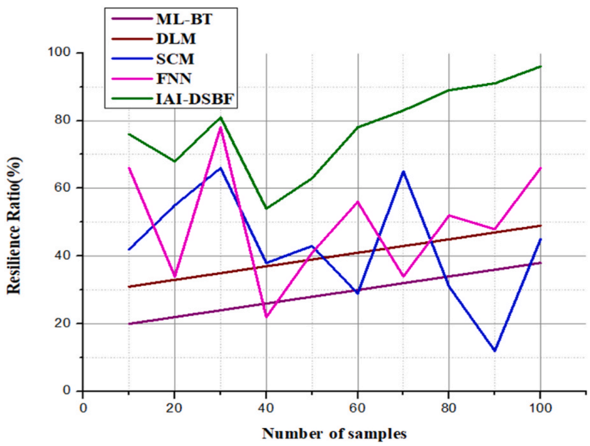

Fig. 10. Resilience analysis for IAI-DSBF and other approaches.

predictions.

The IAI-DSBF model may also be set up quickly since the data collecting and loading processes in these models are easy. AI-based methods for improving building energy efficiency have certain limits. For instance, estimating the structure's energy performance is hard if the building's design or operation changes since these models don't explicitly relate the actual building characteristics to the model inputs. Also, suppose there are changes to the building envelope, system, or operation. The models must be re-trained since AI-based systems need much training data to construct models and keep the forecast quality high. The application's type and amount of input parameters need to be reduced to include IAI-DSBF technologies in building energy conservation procedures. The prediction model stands to gain significantly from the addition of occupancy data. The building's energy consumption is significantly impacted by occupancy characteristics, which include the kind and quantity of inhabitants and their activities. The findings may not be relevant to other types of buildings because the testing was done in just one AI-driven smart building with a specific layout, occupancy pattern, or environment. There was a lack of consideration for deeper behavioral patterns or environmental variables that may impact building performance. The Internet of Things (IoT) sensors could only measure essential ecological variables like temperature, humidity, and occupancy. To create a more comprehensive dataset that might assist in creating more universally applicable AI models, it is crucial to broaden the scope of the study to incorporate many smart buildings with varied designs, occupancy patterns, and geographical locations. To enhance the data acquired, more sophisticated sensor technologies might be utilized to track air quality and real-time energy usage. This allows for a more comprehensive understanding of the building's performance and the health of its inhabitants.

CRediT authorship contribution statement

M. Arun: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Debabrata Barik:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sreejesh S.R. Chandran:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Seepana Praveenkumar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kapura Tudu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Ethics approval statement

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Permission to reproduce material from other sources

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Clinical trial registration

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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